Running Heading: Holt-Winters Forecasting in Healthcare

Holt-Winters Forecasting: A Study of Practical Applications for Healthcare Managers

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Healthcare managers often encounter the need for accurate and reliable forecasts. Decisions about staffing, purchasing, and healthcare delivery depend on the ability to analyze data and predict future observations. Qualitative methods can help with strategic planning in a changing environment; however, quantitative techniques may prove more appropriate in some cases. A basic understanding of forecast modeling can save valuable time and resources. This study demonstrates the use of the Holt-Winters model on common healthcare data series.

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Abstract

Healthcare managers often encounter the need for accurate and reliable forecasts. Decisions about staffing, purchasing, and healthcare delivery depend on the ability to analyze data and predict future observations. Qualitative methods can help with strategic planning in a changing environment; however, quantitative techniques may prove more appropriate in some cases. A basic understanding of forecast modeling can save valuable time and resources. This study demonstrates the use of the Holt-Winters model on common healthcare data series.

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Introduction

Healthcare managers often encounter the need for accurate and reliable forecasts. Decisions about staffing, purchasing, and healthcare delivery depend on the ability to analyze data and predict future observations. Many times managers rely on qualitative methods based on judgment, experience, and intuition. Although organizations may reap immeasurable benefit from these methods, the use of quantitative methods may be more useful to managers who are seeking to improve accuracy of predictions while keeping the costs associated with development and use of forecasting models fixed or minimized.

The purpose of this study is to examine a quantitative business forecasting model using the process of exponential smoothing called the Holt-Winters method. Once explained, this study will demonstrate the Holt-Winters method and compare measures of accuracy using two distinct data series.

Conditions that Prompted Study

Healthcare managers have been observed using everything from guesswork and informal polling to advanced quantitative modeling in order to perform forecasting activities. Although the usage frequency of quantitative methods among healthcare managers is unknown, it may be assumed that qualitative approaches are common and are not without benefits. Most tools have quantitative aspects, but contain significant qualitative utility. Environmental analysis tools include Delphi which uses the solicitation of expert opinion. Brainstorming, focus groups, and nominal group technique are also more qualitative in nature. They involve discussions by interactive groups and can be used to forecast. Scenario analysis is another process for analyzing potential outcomes and contains both quantitative and qualitative elements. It allows managers to investigate the range of potential outcomes. Although quantitative measures are used in scenario analysis, its true value is in exploring qualitative considerations. Ginter, Swayne, and Duncan (2002) explain that tools such as scenario analysis are useful in changing environments and provide a context for strategic thinking. "Scenarios avoid the need for single-point forecasts by allowing users to explore several alternative futures" (Ginter et al, 2002, p.83). However, using qualitative methods to derive predictions when a quantitative approach is more appropriate can lead to serious inaccuracies. The lack of accuracy is a major problem with qualitative methods and many quantitative methods provide more accurate predictions without substantial costs (Pate, 2005).

Quantitative methods include simple and multiple regression techniques, moving averages, and exponential (smoothing) methods. Because some of these techniques require statistical software and expertise beyond the capabilities of many organizations, managers may find that the benefits of investing in these capabilities through outsourcing and additional training are well worth the costs. In other cases, managers have the necessary resources, yet lack an appreciation of quantitative forecasting methods. This study aims to inform healthcare managers of the Holt-Winters method, which is an accessible and powerful forecasting technique. The technique can be developed and used on widely available software applications such as Microsoft Excel® and provides a cost-effective way to conduct healthcare forecasts without tremendous expense and expertise. An additional purpose of this study is to bring an awareness of the application of forecasting in healthcare management and encourage healthcare educators to include economic forecasting in graduate programs.

Problem Statement

The Holt-Winters method has been widely implemented in computer forecasting software and is available to many healthcare managers and leaders. It will be described in detail later, but it is important to recognize its potential usefulness in solving common healthcare management dilemmas. An objective of this paper is to increase awareness of quantitative forecasting techniques in general and the Holt-Winters method in particular. This paper is intended for the professional healthcare manager with little exposure to econometric modeling. The research question here is how can the Holt-Winters method be applied to common forecasting requirements in healthcare organizations?

Literature Review

Forecasting is a dynamic and exciting area of economic study and it has extensive potential applications in healthcare. The goal of health economics is "...to promote a better understanding of the economic aspects of healthcare problems so that corrective health policies can be designed and proposed" (Santerre & Neun, 2004, p. 4). Health economics involves the application of various micro and macroeconomic tools and theories. These theories describe economic activity or behavior, and are often general in nature. For example, economic models are almost never used to determine the actual market price using the most elementary supply and demand model. Hyman (1994) states, "These models are not applied models. They are meant to merely represent a type of consistent economic behavior either visually or mathematically. They provide a 'picture' of that behavior" (p. 11). Econometric forecasts are similar in that they supply predictions that cannot be 100% accurate. "All models contain variables that the model cannot predict because they are determined by forces 'outside' the model" (Hymans, 2005, ¶. 5). Some attempts at forecasting reveal statistical evidence that a data series is almost completely stochastic or follows a random walk. This too is important information for a healthcare professional responsible for managing scarce resources. Although forecasting produces predictions, it is important to remember that those predictions are based on previous observations and are not guaranteed to be perfect. "Forecasting is actually looking into the past; like driving while looking in the rear—view mirror" (T. Carroll, personal communication, February 23, 2006). However, quantitative forecasting models provide healthcare managers with practical tools they can use to develop relatively accurate predictions.

Forecasting is vital to decision-making and strategic planning. Countless industries have used forecasting models to determine such things as expected sales or inventory levels. Pate (2005) suggests that healthcare leaders can gain critical business information through the development of econometric models to evaluate the complex relationships between productive outputs and predictors. Most industries have multiple product lines and have many requirements for forecasting. Healthcare is no different. Managers can utilize forecasting methods to estimate future health plan enrollment, outpatient visits, laboratory tests, radiological images, and pharmaceutical stocks. Such data are becoming increasingly available and healthcare managers can use statistical analysis to turn the data into information. Skrepneck (2005) discusses the opportunity for the application of statistics in healthcare.

> The increased availability of administrative databases containing medical and pharmacy claims data may provide those in managed care settings with a greater ability to evaluate treatments and practice patterns. Given that administrative data are observational rather than experimental, it is critical that analysts and decision makers be versed in appropriate statistical methods to design investigations or evaluate empiric findings (p. 250).

Skrepnek's article is among few pieces of professional literature that specifically applies econometric models to healthcare management. Literature describing quantitative forecasting in healthcare is even rarer; however, many examples of forecasting in healthcare exist. One such example is a study conducted by hospitals in Ontario that used population forecasts to determine the future incidence of mechanical ventilation. The study, completed in 2005, projected the incidence through 2026 in order to "understand the impact of aging baby boomers on critical care resources" (Needham et al., 2005, p. 574). The researchers applied existing incidence data derived from billing and insurance plan databases to Census-based Ontario population data. Although the annually compounded growth rate is expected to be consistent with previous years, the researchers estimated an 80% increase in the number of ventilated patients by 2026. Such information is important to entities like Intensive Care Units (ICU). “Given the specialized human and capital resources required, ICUs have much less flexibility than other hospital units to adjust to growth” (Needham et al., 2005, p. 577). Forecasts are necessary because advanced planning is essential to adequate staffing and financing.

Another example of quantitative forecasting in healthcare comes from the Military Healthcare System (MHS). Within the MHS, leaders and researchers have access to the Managed Care Forecasting and Analysis System (MCFAS), which is the official tool for predicting MHS-eligible beneficiary populations. MCFAS methodology involves creating cohorts of beneficiary groups such as active duty, family members, and retirees. Demographic information is collected on the cohorts in order to generate forecasts of the physical locations of beneficiaries by zip code. The model then computes the eligible beneficiary population by using weighted quarterly averages. Once averages are calculated, beneficiaries are assigned to the market area of a Military Treatment Facility (MTF). The resulting forecasts allow MTFs to manage the care provided to eligible patients in their market areas. MCFAS data are useful when developing marketing and business plans, providing input for population health initiatives, and planning for medical facility construction among other things. The transient nature of military beneficiaries poses a unique challenge to the accuracy of MCFAS. As mentioned earlier, forecasting models rarely achieve absolute precision. However, accuracy is important because errors can be expensive in terms of cost and time.

"Forecast accuracy is important because a high forecast leads to excessive inventories, and a low forecast leads to stockouts" (Holt, 2004). Although accuracy of the model is important, healthcare managers must also remember that no forecasting method has zero error. "Studies have shown that forecasts that combine the model and the forecaster's judgment are generally more accurate than 'purely objective' forecasts that are produced with the econometric model alone" (Hymans, 2005, ¶. 15).

Although healthcare managers have a number of forecasting methods to choose from, they must carefully select the best method given the context of the problem and the data available to support analysis. When selecting a model, one should consider the level, trend, and seasonality of the data. Additionally, some models are more or less appropriate for short or long term forecasting. Healthcare managers often evaluate time-series data. "A time series is a sequence of observations which are ordered in time or space" (Statistics Glossary, 2005, ¶. 1). Time series data often display some degree of randomness. Forecasting methods commonly used with time-series data are considered deterministic because "no reference is made to the sources or nature of the underlying randomness in the series. Essentially, the models involve extrapolation techniques that have been standard tools of the trade in economic and business forecasting for years" (Pindyck & Rubinfeld, 1998, p. 467). Methods include moving averages, regression analysis, and smoothing techniques.

The Holt-Winters method uses a technique called exponential smoothing, which is "used to reduce irregularities in time series data, thus providing a clearer view of the true underlying behavior of the series. It also provides an effective means of predicting future values of the time series" (Statistics Glossary, 2005, ¶. 7). "At times it is desirable to smooth a time series and thus eliminate some of the more volatile short-term fluctuations" (Pindyck & Rubinfeld, 1998, p. 467). An important characteristic of exponential smoothing is that weights are applied to past values. Weights can be set so that the most recent and therefore most relevant observations are given more weight than those observed further in the past. Models involving exponential smoothing are particularly helpful because "the predicted value is updated each time new information becomes available at the end of a series" (National Statistics United Kingdom [NSUK], 2005). These methods provide healthcare managers with the ability to make predictions using the most current and relevant data. Healthcare is an ever-changing industry, which makes real-time forecasting even more important.

Recognizing a need for a practical technique to forecast sales, Holt extended the concept of exponentially weighted moving averages to forecast multiple components of a variable. Holt (2004) explains that he found that components such as trend and seasonality could be forecasted and he created a system that had several exciting characteristics. Holt noted that the method "...was easy to program, fast to compute, required minimal data storage, put declining weight on old data, used simple initial conditions, had robust parameters, was automatically adaptive, model formulations were easy, and the math was tractable" (p. 124). To determine the accuracy of Holt's method, a graduate student by the name of Winters tested the new model by programming "...the formulas in FORTRAN for an IBM 650 [10] and found that the formula forecasts were surprisingly accurate" (Holt, 2004, p.124). Winters went on to publish his results and the formulas became known as the Holt-Winters method.

Method and Procedures

Setting

The study originates at the Mike O'Callaghan Federal Hospital (MOFH) located near Nellis Air Force Base, Nevada. The MOFH is a joint venture between the Department of Defense (DoD) and the Veterans Health Administration (VHA). It serves a population of over 300,000 eligible beneficiaries both military and veteran. Situated in the Las Vegas valley, one of the fastest growing regions in the United States, the MOFH is facing demand for healthcare beyond current capacity. The military population is expected to grow with DoD Base Realignment and Closure Commission decisions to increase troop levels at Nellis. The veteran population is likewise expected to increase and many will require VHA care as the incidence of service related injuries and illnesses rises. A 2006 Air Force Times article reported that in fiscal year 2005, more than 23,000 service members with physical injuries or other conditions went through the military disability evaluation system; a 55% increase from 2001. MOFH functions such as business planning, financial management, and manpower can all benefit from quantitative forecasting techniques. Forecasting models that review past behavior can be combined with future expectations to create a reliable basis for planning. The analysis examined two data series and evaluated accuracy using both series. The first represents monthly prescriptions of pseudoephedrine. Pseudoephedrine is a drug commonly prescribed to relieve nasal congestion and other cold and flu symptoms. It belongs to a group of drugs called sympathomimetic agents and is usually found in such over-the-counter medications as Sudafed. However, military providers prescribe the medication and it is dispensed in military pharmacies. The second series consists of monthly outpatient visits resulting in a diagnosis of Upper Respiratory Infection (URI). URIs are often treated with pseudoephedrine among other medications. URIs include pharyngitis, sinusitis, epiglottitis, laryngotracheitis, common cold, viral upper respiratory tract infection, bacterial respiratory infection, and group A streptococci among others. The monitoring of visits associated with URI is important because of the highly contagious nature of many conditions. The data series were selected because of the close association between URI and psudoephedrine use and their commonness in primary care settings worldwide.

This study evaluated 42 months of data covering fiscal years 2004 through 2005 and the first half of fiscal year 2006. Once the model was identified, there was a fitting period of 39 months and an evaluation period of three months. The evaluation period was January 2006 to March 2006. The Holt-Winters method was used because both data series contain trend and seasonal variation. "Holt-Winters has an additive and a multiplicative form. The additive method was used in this study because "...the seasonal effect does not depend on the current mean level of the time series" (Koehler, Snyder, & Ord, 2001, p. 269). "In other words, the magnitude of the seasonal pattern does not change as the series goes up or down" (Minitab Statistical Software v. 14).

The exponential smoothing technique used in the Holt-Winters method requires a smoothing constant set in the range $0 < \alpha < 1$. This constant is used to apply weights to the observations as described earlier. The optimal value of the smoothing constant varies based on the time-series data in question. It is "commonly set between 0.05 and 0.3, although it is possible to estimate α by minimizing the sum of squared prediction errors" (NSUK, 2005). Some statistical software programs calculate the optimal values of the smoothing constants by minimizing Σe^2. More basic smoothing techniques such as single and double exponential smoothing use optimal values after an Autoregressive Integrated Moving Average (ARIMA) analysis estimates the length and value of the smoothing parameters. Minitab® does not provide optimal smoothing parameter values for the Holt-Winters method because "...an equivalent ARIMA model only exists for a very restricted form of the Holt-Winters model" (Minitab Statistical Software v. 14). The value of the weight for each component can be changed according the characteristics of the time series data. "A high value of α will lead to the majority of the weight being placed on the most recent observations whereas a low value of α will mean that observations further in the past will gain more importance" (National Statistics United Kingdom, 2005, ¶. 6) The additive Holt-Winters model involves smoothing each component of level, trend, and seasonality. Mathematically, it is written as:

$$M_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(M_{t-1} + R_{t-1})$$
$$S_t = \beta(Y_t - M_t) + (1-\beta)S_{t-s}$$
$$R_t = \gamma(M_t - M_{t-1}) + (1-\gamma)R_{t-1}$$
$$F_{t+1} = M_t + hr_t + S_{t-s-h}$$

The smoothing constants are represented by α, β, and γ. M estimates the deseasonalized level, S calculates the smoothed seasonal index, and R represents the smoothed trend factor. The last equation is used to forecast the next period. Minitab® statistical software version 14 was used to conduct all analyses. Because it is unknown which statistical software may be available to a particular healthcare manager, it is important to note that forecasting work can be done in multiple software applications including the more sophisticated Eviews® and the more common Microsoft Excel®.

Each data series was assigned two different sets of smoothing parameters. The same model was used for both sets of data, but the model was calibrated by changing the weights or smoothing parameters to determine the version with the lowest error. First, the default parameters from Minitab® were used. Defaults were set at 0.2 for the level, trend, and seasonal components. Then, the weights that created the lowest Mean Absolute Percentage Error (MAPE) were found by iteratively testing values between 0 and 3. The data used in this study were compiled by fiscal month starting in October 2002 and the seasonal period used in both calibrations of the model was 12.

Each set of parameters was applied to the 36 observations of both pseudoephedrine prescriptions and URI encounters. Minitab® then calculated a forecast and confidence intervals for periods 37, 38, and 39. The errors for both calibrations were examined and the one with the lowest MAPE was applied to 39 observations in order to forecast periods 40, 41, and 42 basically creating a new fitting period. When evaluating time series models "...our objective is to develop models that explain the movement of a time series by relating it to its own past values..." (Carroll, 2006). The final forecast was compared to the actual observations for the same periods and results are discussed in this study.

Data Source

Data for this study were gathered from the Military Healthcare System's M2 database. The M2 is a data warehouse that contains data related to demographics, patient encounters, and cost; among other things from every Department of Defense medical treatment facility. Patient specific data were not collected to avoid any ethical dilemmas associated with the ability to identify individuals.

Validity and Reliability

Before examining the method, it is important to discuss the validity and reliability of the data used. Both M2 and MCFAS, the population forecasting tool mentioned earlier, are supported by the Executive Information and Decision Support (EIDS) office of the Military Healthcare System (MHS). "EIDS collects, processes, and manages nearly 100 terabytes of enterprise data through a powerful suite of decision-support tools that enable effective management of MHS health care operations" (EIDS, 2006, p. 1, ¶ 1). M2 is one of several programs produced by EIDS, and it is widely used for its many applications in healthcare management. EIDS (2005) explains M2's usefulness this way:

> M2 is a powerful ad-hoc query tool used to obtain summary and detailed views of population, clinical, and financial data from all MHS regions. M2 includes MTF and purchased care data with eligibility and enrollment data. This integrated data enhances support to decision-makers at all levels of the MHS. With M2, source savvy analysts can perform trend analyses, conduct patient and provider profiling studies, and realize opportunities for transferring health care from the private sector to the Military Treatment Facility (MTF). (¶ 2)

EIDS ensures data quality and consistency by following business rules that have been approved by the medical departments of the Army, Navy, and Air Force. The collection of data is standardized and data are gathered directly from the operating systems of each MTF. Additionally, many other MHS applications use data from M2 in order to assist healthcare managers in decision making. The M2 data warehouse is relied upon by government agencies and individuals alike for the most recent record of administrative and clinical data. That said, the data reflect inputs by individuals and are subject to human error. Regular audits are performed to guard against gross errors and to ensure the best possible data quality.

Evaluating reliability and validity of the Holt-Winters method involves deciding "...whether the forecasting process was reasonable for the situation" (Armstrong, 2001, p. 1). "Validity refers to the extent to which a test measures what we actually wish to measure" (Cooper & Schindler, 2003, p. 231). This study examines construct validity because "construct validity asks whether a measure does, in fact, measure what it purports to measure" (Armstrong & Collopy, 1992, p. 74). To what extent does the model produce accurate forecasts? This is done by comparing the MAPE of each calibration of the model. Another test of construct validity involves determining whether other error measures were similar to the MAPE. Armstrong and Collopy (1992) considered agreement among accuracy measures when testing construct validity. When they evaluated the MAPE with other error measures; they found that depending on the size of the series, the measures each provide reasonable measures of accuracy. In this study Minitab® computes a Mean Absolute Deviation (MAD) and a Mean Squared Deviation (MSD) which both measure the accuracy of fitted time series values. The calibrations with the lower MAPE also produced the lower MAD and MSD.

Reliability is a measure of consistency. It "...addresses the question of whether repeated application of a procedure will produce similar results" (Armstrong & Collopy, 1992, p. 73). This study calculated a three month ahead forecast from 36 observations and then a different sample was created when the actual values for the three months were added to the original sample. Again, the calibration with the lower error was applied to the new sample of 39 observations in order to derive a forecast for periods 40, 41, and 42. Reliability was assessed by examining the extent to which the MAPE of the first sample was similar to the MAPE of the second sample when the same calibration of the model was applied to both samples. This approach was demonstrated by Armstrong and Collopy (1992) when they used MAPE in the determination of reliability. MAPE and other error measures were ranked by accuracy and then tested to determine whether they produced the same accuracy rankings when applied to different samples from a set of time series.

Results and Discussion

The following section contains results from the various calibrations of the model and forecasts of both pseudoephedrine prescriptions and URI visits. First, a model to forecast pseudoephedrine is determined and the predicted values are compared with actual ones. The same is done for URI visits.

Table 1

Holt-Winters smoothing parameters and Mean Absolute Percentage Errors: Pseudoephedrine prescriptions

Smoothing Parameters	MAPE
Level 0.20, Trend 0.20, Seasonal 0.20	14.597
Level 0.25, Trend 0.25, Seasonal 0.25	13.255

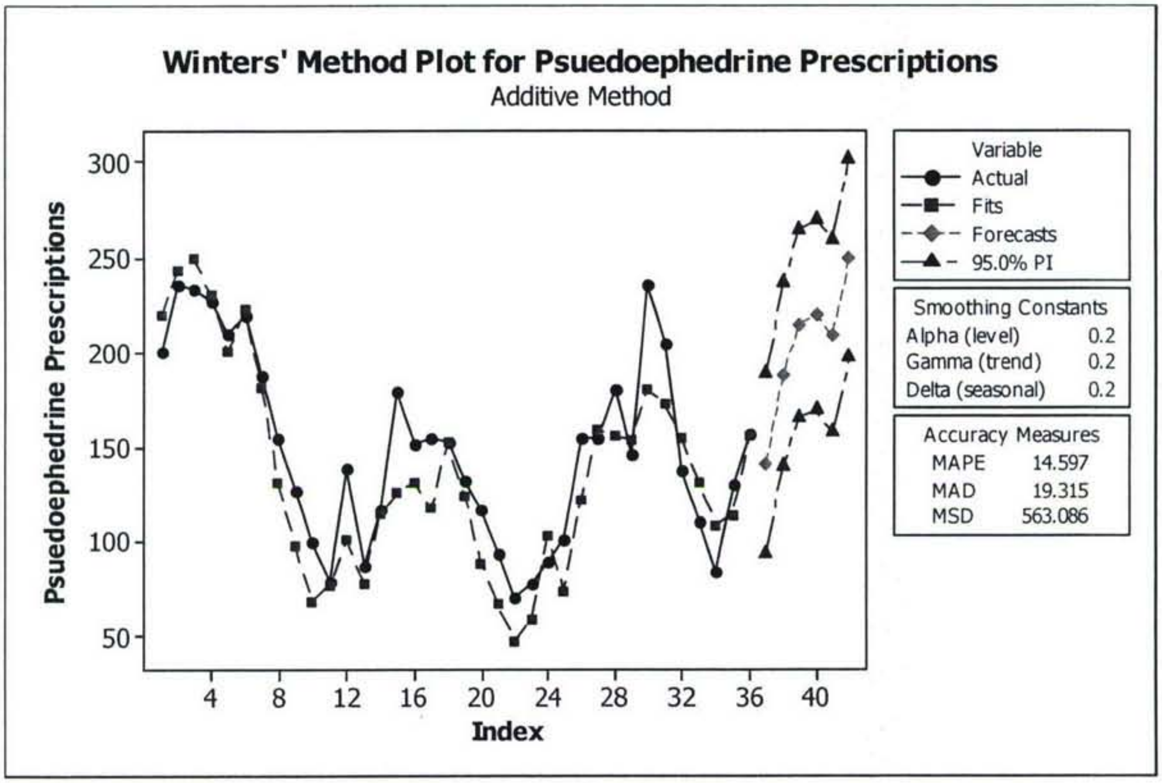

Figure 1. Line Plot of Pseudoephedrine Prescriptions forecast using smoothing parameters = 0.2 and 36 observations

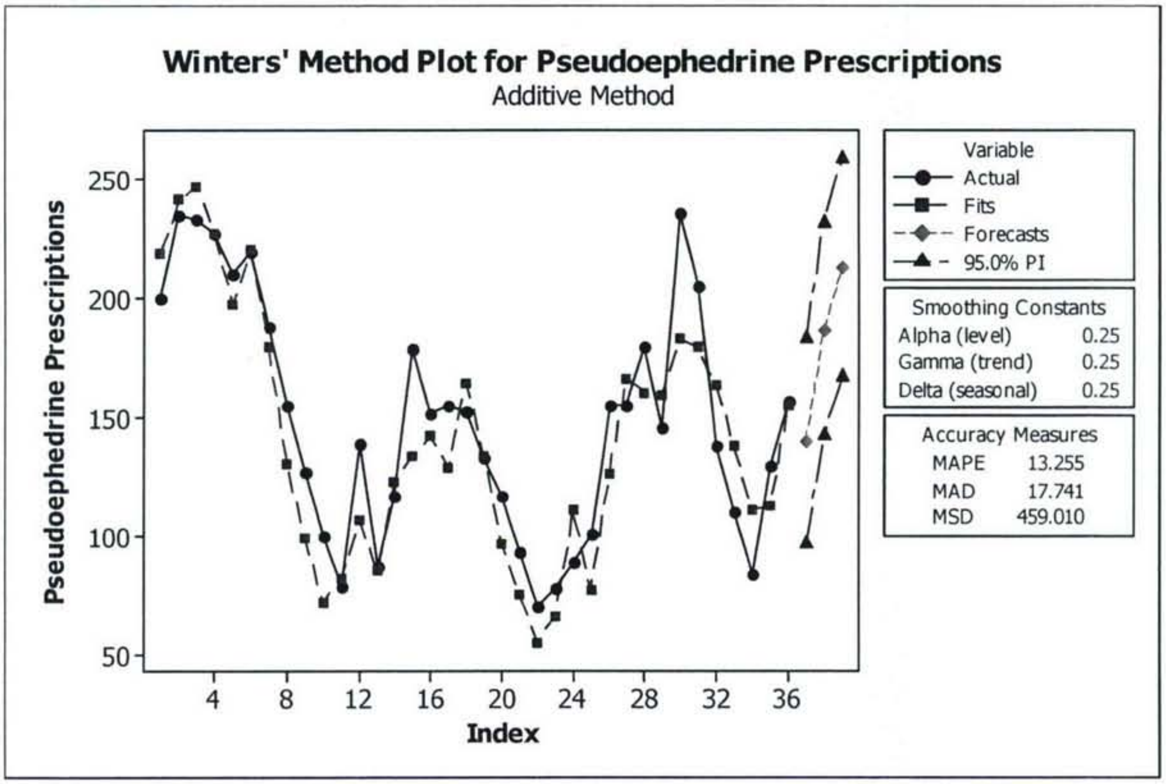

Figure 2. Line Plot of Psuedoephedrine Prescriptions forecast using smoothing parameters = 0.25 and 36 observations

The Holt-Winters calibration which assigned smoothing parameters of 0.25 produced the lower MAPE when evaluated with 36 months of data. The actual values for periods 37, 38, and 39 were then added to the sample and the 0.25 calibration was applied to a series of 39 observations. The resulting forecast predicted pseudoephedrine prescriptions for periods 40, 41, and 42.

Table 2

Holt-Winters Forecast of Psuedoephedrine prescriptions with smoothing parameters = 0.25 and 95% confidence intervals

Period	Forecast	Upper	Lower
40	241.479	189.969	292.990
41	232.609	179.827	285.392
42	275.708	221.479	329.937

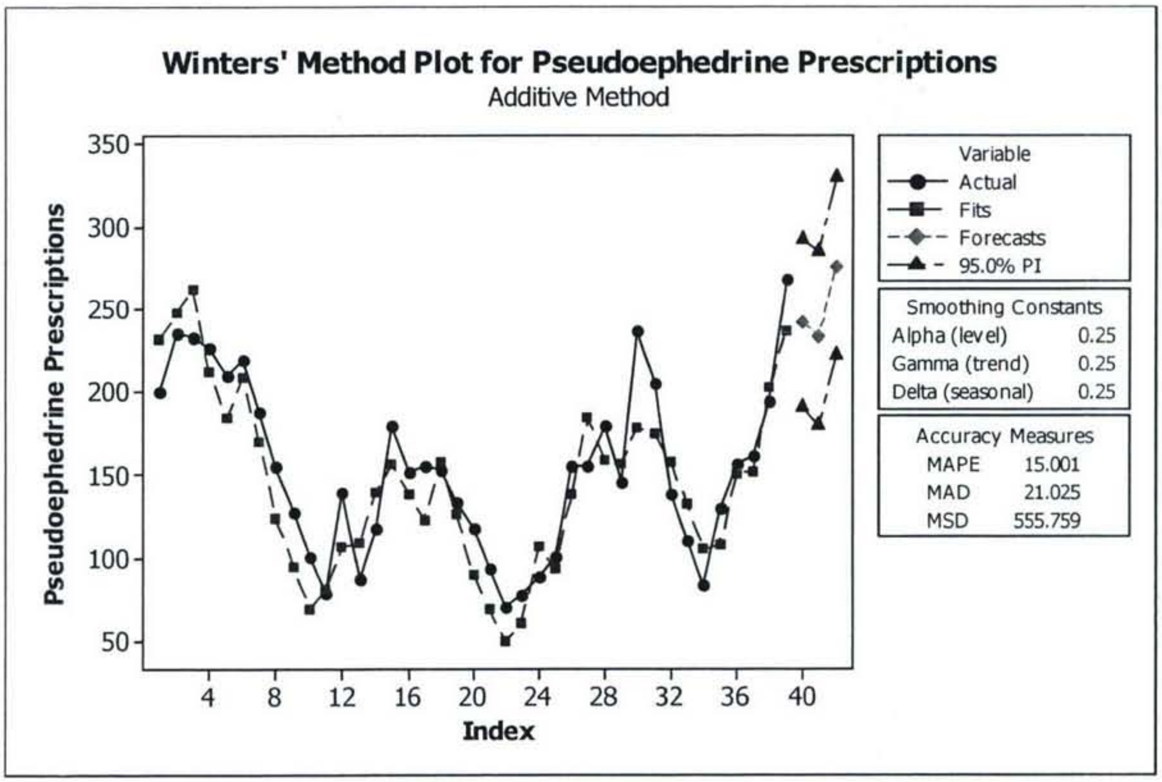

Figure 3. Line Plot of Psuedoephedrine Prescriptions forecast using smoothing parameters = 0.25 and 39 observations

The actual number of pseudoephedrine prescriptions for periods 40, 41, and 42 were 239, 181, and 216 respectively. The in-sample MAPE was 15.001. Although larger than the MAPE of the original fitting period (13.255), it is not significantly different and indicates a reliable model. Also, the actual values are relatively close to the predicted values. However, the stochastic nature of the data is apparent in the wide confidence intervals.

The next section follows the forecast of another time series. Visits for Upper Respiratory Infection (URI) are common in primary care settings. URI visits may result in prescriptions for such medications as pseudoepherine and managers would benefit from the ability to produce short term forecasts for planning purposes.

Table 3

Holt-Winters smoothing parameters and Mean Absolute Percentage Errors: URI visits

Smoothing Parameters	MAPE
Level 0.20, Trend 0.20, Seasonal 0.20	18.5
Level 0.15, Trend 0.15, Seasonal 0.15	18.1

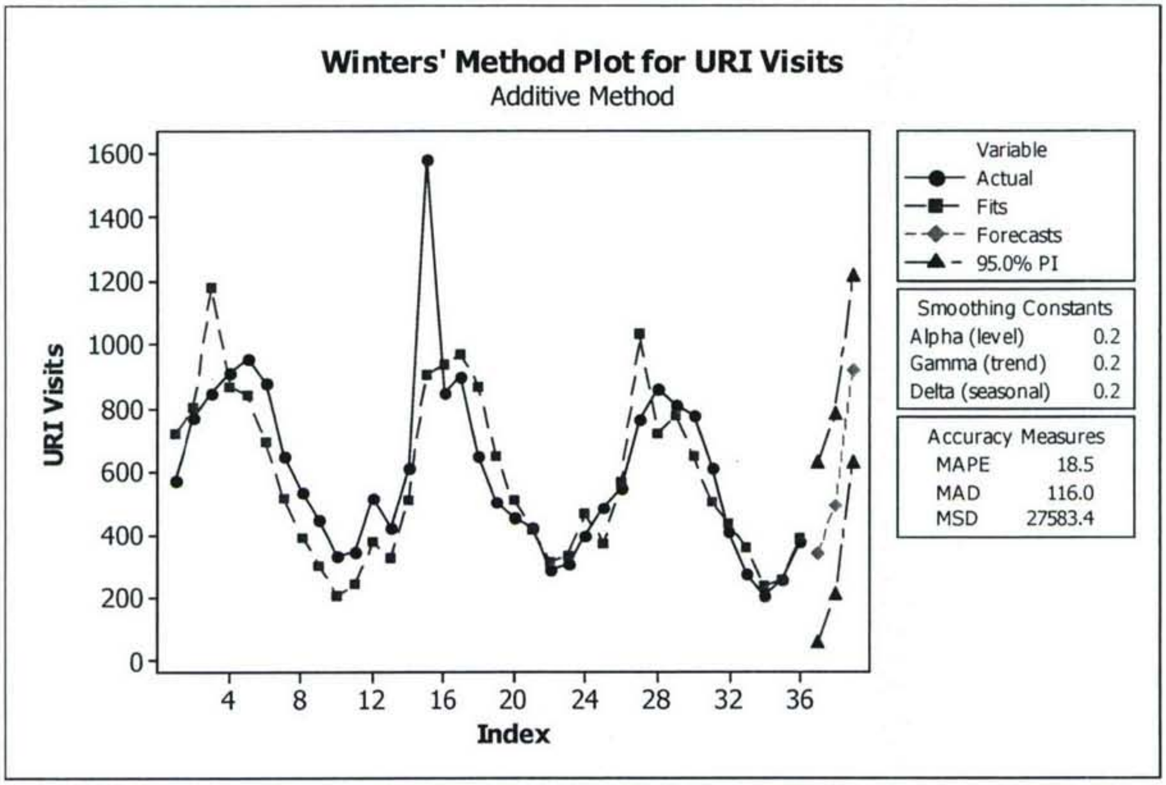

Figure 4. Line Plot of URI visits forecast using smoothing parameters = 0.2 and 36 observations

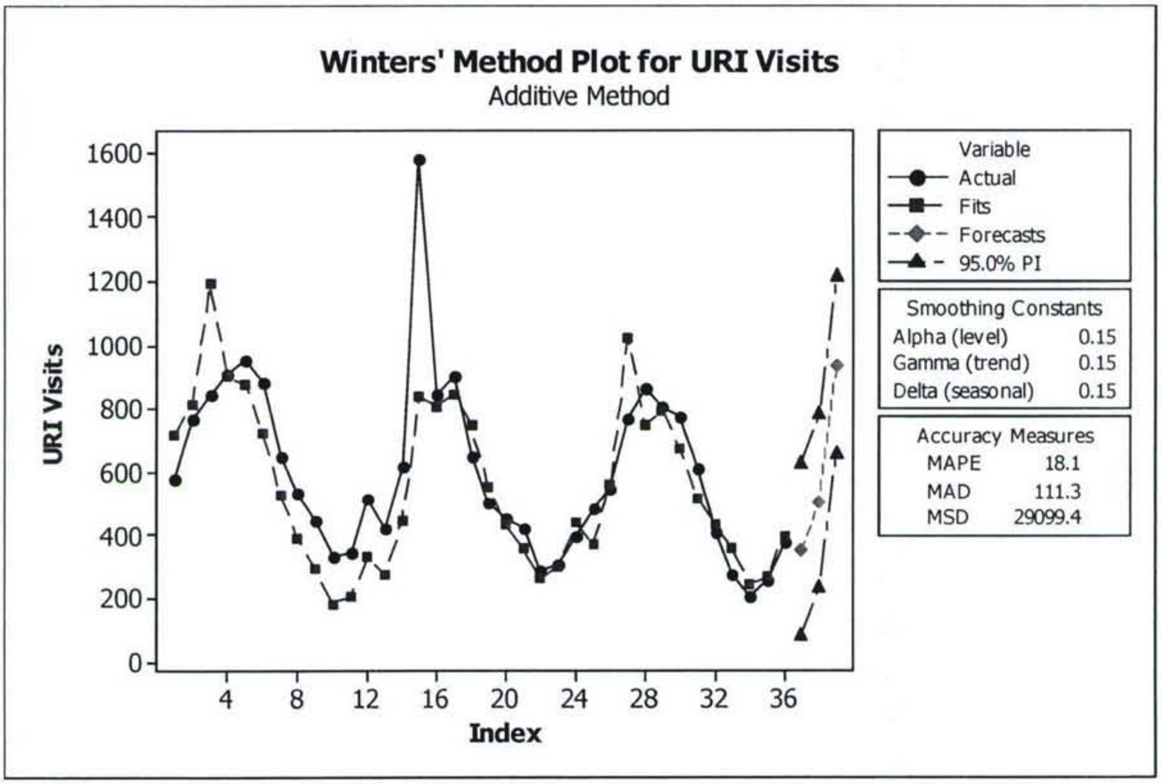

Figure 5. Line Plot of Upper Respiratory Infection visits forecast using smoothing parameters = 0.15 and 36 observations

The calibration which assigned smoothing parameters of 0.15 produced the lower MAPE when evaluated with 36 months of data. The actual values for periods 37, 38, and 39 were then added to the sample and the 0.15 calibration was applied to a series of 39 observations. The resulting forecast predicted URI visits for periods 40, 41, and 42.

Table 4

Holt-Winters Forecast of URI visits with smoothing parameters = 0.15 and 95% confidence intervals

Period	Forecast	Upper	Lower
40	790.498	524.943	1056.05
41	812.102	544.229	1079.97
42	701.322	430.922	971.72

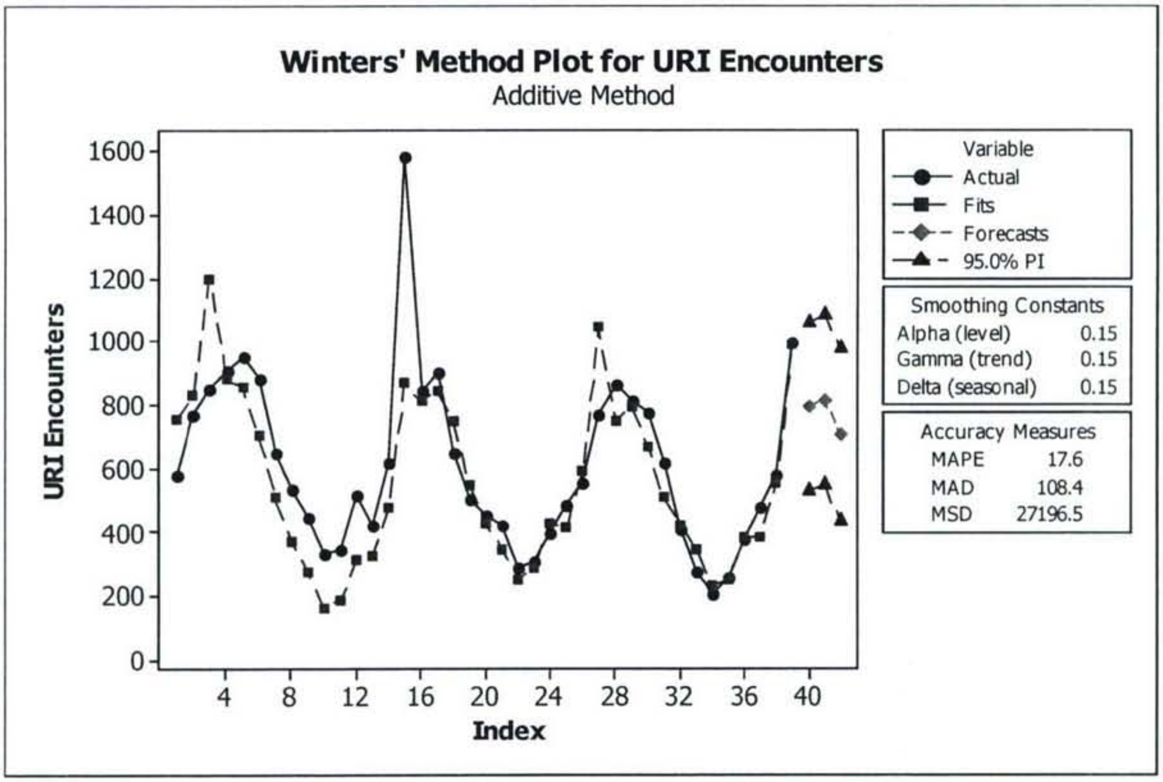

Figure 6. Line Plot of Upper Respiratory Infection visits forecast using smoothing parameters = 0.15 and 39 observations

The actual number of URI visits for periods 40, 41, and 42 were 677, 584, and 532 respectively. The in-sample MAPE was 17.6. Although smaller than the MAPE of the original fitting period (18.1), it is not significantly different and indicates a reliable model. In this case, however, the actual values seem quite different from the predicted values although they fall within the confidence intervals. Several explanations may exist for the discrepancies. For example, there may be some assignable variance in recent months that the model cannot account for, or the randomness of the time series was underestimated. Still, familiarization with quantitative forecasting methods can arm the healthcare manager with the ability to make simple forecasts and avoid more costly analyses.

Conclusions and Recommendations

The objective of this study was to shed light on the possible applications of quantitative forecasting in healthcare by demonstrating the Holt-Winters method on two series of healthcare data. With an introduction to forecasting techniques, healthcare professionals can create simple models to address common problems or conduct short term planning.

The utility of this and other forecasting methods is extensive as shown by current examples in healthcare. The military's MCFAS for example was created in response to the need for predictions about future populations. Forecasting techniques can be used by healthcare professionals at all levels who are involved with policy analysis, strategic planning, or basic decision-making. Models can be used to predict time-series data related to resource management, clinical care, logistics, and ancillary services.

This study examined a model to forecast Pseudoephedrine prescriptions and URI visits. However, forecasting not only aids in pharmacy and clinical management, it can help identify spikes in usage and make managers aware of trends. Unfortunately, it may be important for healthcare professionals to study psuedoephedrine use because of potentially serious side effects and its illegal use in methamphetamine production. Even when the recommended dosage is taken, pseudoephedrine can cause adverse cardiovascular effects such as "...hypertension, arrhythmias, prolongation of the QT interval, and angina pectoris" (Manini, Kabrhel, & Thomsen, 2005, p. 213). Pseudoephedrine is a main ingredient in the illegal drug methamphetamine also known as meth. Meth is manufactured in makeshift laboratories throughout the US and there are approximately 1.4 million meth users in America. That number is rising and a 2005 study found "...58 percent of law enforcement officials in 500 counties surveyed by the National Association of Counties cite methamphetamine as their biggest drug problem" (PBS, 2006). Internationally, meth is considered the most abused hard drug. "The world's 26 million meth addicts equals the combined number for cocaine and heroine abusers" (PBS, 2006). Meth triggers dopamine which results in a prolonged euphoria. It is extremely addictive and over time can lead to many serious medical conditions such as stroke, heart attack, seizure, and death.

Over 35 state legislatures have restricted the sales of products containing pseudoephedrine. In Oregon, pseudoephedrine must be prescribed. The Minnesota House of Representatives overwhelmingly approved a ban on over-the-counter sales of tablets containing pseudoephedrine in 2005 making it one of the strongest meth bills in the country. Critics are concerned that the bill goes too far and that legitimate uses for the drug are overlooked, making it harder for patients to obtain inexpensive cold therapies. In Minnesota, the ban only applies to the pill form that is easily cooked and transformed into meth. Liquid and gel caps will still be available on the market. The effects of meth are devastating and the byproducts are extremely toxic. The epidemic concerns law enforcement, environmentalists, politicians, healthcare professionals, and practically the whole of society.

Many opportunities exist for future study. Additional research could include the demonstration of other forecasting models such as moving averages or autoregressive models. These models also relate a series to its own past values and are useful in forecasting time series data.

Another opportunity for further study is the use of quantitative forecasting in health law. Some states allow economists to project hedonic damages in wrongful death and medical malpractice cases. Forensic economics involves using financial and statistical models to determine the value of such things as the loss of enjoyment of life. Forecasts are conducted to estimate lost earnings, the cost of future healthcare, even the loss of companionship for survivors. Increasingly, states are allowing testimony from economists on the value of many variables related to damages. Many elements of damage are already allowed under the law, however, "...until recently, jurors were left to their own unpredictable estimations of additional values" (Smith, 1990, p. 48). Although such economic analysis may be beyond the scope of your average healthcare manager, an understanding of health law and related topics is important for a successful healthcare professional.

Quantitative forecasting techniques such as the Holt-Winters method are not simply numbers from thin air. They "consist of intuitive judgments throughout the modeling process" (Pindyck & Rubinfeld, 1998, p. 13). It involves statistical analysis, which is as much an art as a science. Healthcare managers are not as familiar as they could be with very basic tools that can save a lot of time and resources. Graduate healthcare administration programs should incorporate additional and expanded health economics courses in their curricula. Students and graduates will not predict the future with absolute certainty, but they will be able to build and use models that allow them to come close.

References

Armstrong, J. S. (2001). Standards and practices for forecasting. *Principles of Forecasting: A Handbook for Researchers and Practitioners*, 1-46.

Armstrong, J. S. & Collopy, F. (1992). Error measures for generalizing about forecasting methods: empirical comparisons. *International Journal of Forecasting*, 8, 69-80.

Cooper, D.R. & Schindler, P.S. (2003). *Business Research Methods.* New York, NY: The McGraw Hill Companies, Inc.

Disability cases grow. (2006, April 24). *Air Force Times,* p. 6.

Executive Information and Decision Support for the MHS. (2004). *MCFAS 4.02 Beneficiary Population Forecasting Model User Manual* (Publication No. 10574.004 WP 04-4). Falls Church, VA: Author

Executive Information and Decision Support for the MHS. (2005). *MCFAS Methodology Overview.* Falls Church, VA: Author

Ginter, P.M., Swayne, L.E. & Duncan, W.J. (2002). *Strategic Management of Health Care Organizations.* Oxford: Blackwell Publishing Ltd.

Holt, C. C. (2004). Forecasting seasonals and trends by exponentially weighted moving averages. *Journal of Economic and Social Measurement*, 29, 123-125.

Hyman, D. (1994). *Macroeconomics (3rd ed.).* Burr Ridge, IL: Irwin.

Hymans, S. H. (2005). *Forecasting and Econometric Models.* Retrieved October 9, 2005, from http://www.econlib.org/library/Enc

Kalekar, P. S. (2004). *Time Series Forecasting using Holt-Winters Exponential*

Smoothing. Unpublished doctoral dissertation, Kanwal Rekhi School of Information Technology.

Koehler, A.B., Snyder, R.D., & Ord, J.K. (2001). Forecasting models and prediction intervals for the multiplicative Holt-Winters method. *International Journal of Forecasting*, 17, 269-286.

Manini, A.F., Kabrhel, C., Thomsen, T.W. (2005). Acute myocardial infarction after over-the-counter use of pseudoephedrine. *Annals of Emergency Medicine,* 45, 213-216.

Military Healthcare System M2 Database: 2006

- *Number of URI visits and Pseudoephedrine prescriptions in fiscal years 2004-2005* [Data file]. Falls Church, VA: TRICARE Management Activity

Minitab Statistical Software (2005). State College, PA.

National Statistics United Kingdom. (2005). *Methodology of the Experimental Monthly Index of Services.* Retrieved September 21, 2005, from http://www.statistics.gov.uk/iosmethodology/default.asp

Needham, D.M., Bronskill, S.E., Calinawan, J.R., Sibbald, W.J., Pronovost, P.J., & Laupacis, A. (2005). Projected incidence of mechanical ventilation in Ontario to 2026: Preparing for the aging baby boomers. *Critical Care Medicine*, 33(3), 574-579.

Pate, C.L. (2005, September). *Exponential Smoothing Methods and Healthcare Workload: A Case Study of Primary Care Visits.* Paper presented at The 27th Australian Conference of Health Economists

Pindyck, R.S. & Rubinfeld, D.L. (1998). *Econometric Models and Economic*

Forecasts. Singapore: Irwin McGraw-Hill

Public Broadcasting System. (2006). *Frontline: The Meth Epidemic*. Retrieved March 24, 2006, from http://www.pbs.org/wgbh/pages/frontline/meth/faqs/

Santerre, R.E. & Neun, S.P., (2004). *Health Economics: Theories, Insights, and Industry Studies*. Mason, OH: Thomson South-Western.

Skrepnek, G.H. (2005). Regression methods in the empiric analysis of health care data. *Journal of Managed Care Pharmacy*, 11, 240-251.

Smith, S.V. (1990). Hedonic damages in the courtroom setting – a bridge over troubled waters. *Journal of Forensic Economics*, 3(3), 41-49.

Statistics Glossary. (2005). *Time Series Data*. Retrieved September 30, 2005 from http://www.stats.gla.ac.uk/steps/glossary/time_series.html